Application of a metallurgical enterprise information system for collection and analysis of big data and optimization of multi-agent resource conversion processes

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Abstract

Solving the problem of processes management in organizational and technical systems implies, the collection and analysis of large amounts of data from various departments and production areas coming from heterogeneous information systems. A metallurgical enterprise information system ensures data collection and storage, data preparation for decision-making using machine learning methods, and decision-making using simulation and heuristic methods. The proposed methods of decision-making allow non-programming users to generate and evaluate various alternatives of the system operation and choose one alternative based on the described criterion. These methods have been applied to solve the problem of optimizing the processes of implementing measures to prevent incidents at the enterprise.

Keywords: MEI system, hybrid decision-making method.

1 Introduction

Recently more attention is paid to processes management in organizational and technical systems. Large industrial enterprises are implementing MES and ERP-systems, digitizing the production, realizing the material tracking, and implementing an analytical study of historical data on production and orders. Development of a system of fully digitized production with opportunity of production processes optimization and decision-making support is relevant.

The paper is devoted to the description of a hybrid decision-making method on the basis of simulation and heuristic evolutionary modeling. This method is implemented in a modeling subsytem of a metallurgical enterprise information system (MEI system) [1-5]. The MEI system is solved the problem of fully digitized production. The MEI system is designed for analysis of production using simulation models of multi-agent resource conversion processes (MRCP) [6] and real-time management decisions using BIG DATA technology [7].

We consider the structure of the MEI system and extension of the MRCP model of the modeling subsystem of the MEI system using the evolutionary modeling method to support the processes optimization.

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Table 1: Comparative analysis of the simulation systems

Comparison criterion	AR	G2	ALC	MEI
The language of the resource conversion processes description	YES	YES	YES	YES
Multi-agent modeling	NO	NO	YES	YES
Simualtion	YES	YES	YES	YES
Expert modeling	NO	YES	NO	YES
Evolutionary modeling	NO	NO	YES	YES
Multi-user mode	NO	YES	YES	YES
Carrying out experiments on the server via the Internet	NO	YES	YES	YES
Java support	NO	YES	YES	YES
Orientation to non-programming user	YES	NO	NO	YES
Means of data exchange with CIS, MES-, ERP-systems	NO	YES	NO	YES

2 The metallurgical enterprise information system structure

The MEI system consists of two subsystems: a subsystem of the data collection and a modeling subsystem. The subsystem of the data collection includes: data warehouse, the query builder module [3-5], the data exchange module. The modeling subsystem includes: the data preparation module, the module for creating process models (CM), the module of the processes optimization (PO), the integration module, which solves the problem of using models in decision-making processes in real time. The CM and PO modules of the MEI system have been developed jointly with the Ural Federal University.

Commercial products of the class of simulation systems of technological, logistic, and organizational (business) processes, represented on the market (AnyLogic, Arena, ARIS, G2, Simio), are desktop-applications. In the development of complex simulation models in the team, additional requirements for simulation systems are the following: support for multi-user mode, access to the model and conduct experiments through the Internet. The MEI system uses an approach that is close to cloud computing. Cloud computing [8] is a model for providing convenient network access on demand to a common pool of configurable computing resources that can be provided and released with minimal operating costs and / or calls to the provider.

A comparative analysis of the simulation systems is presented in Table 1: ARIS (AR) [9], G2 [10], AnyLogic Cloud (ALC) [11], and modeling subsystem of the MEI-system.

The main competitive advantage of the modeling subsystem of the MEI system is the availability of the modules for analysis and data preparation, which with the help of machine learning methods work with a large amount of accumulated data and restore the missed data collected from production sensors. In addition, an important advantage of the MEI system is the ability to exchange data (both input data for simulation and simulation results) with various external information systems using a data bus. The competitive advantage is the orientation of the MEI system to the non-programming user, such as technologist, logist, etc.

The MEI system also supports the optimization of the company's processes. Optimization implies generation and evaluation various alternatives of the system operation by simulation and choose of the one alternative based on the described criterion (objective function). Integration of evolutionary and simulation modeling allows to narrow the space of a full-factor experiment with the model and obtain an optimal (effective) solution in less time.

We consider development of a hybrid decision-making method in the MEI system in order to support the optimization of the MRCP processes.

3 Development of a hybrid decision-making method

The MEI system provides an opportunity to build models of MRCP and collective behavior of objects (agents in terms of artificial intelligence). The basis of the MRCP model is queuing schemes, automata, Petri nets and the agent approach [12-13]. The MRCP model is extended by the application of a genetic algorithm (GA) [14], one of the methods of evolutionary modeling. This opportunity provides a wide range of the processes optimization.

The application of the integrated evolutionary-simulation algorithm allows to use the natural laws of the development of complex systems for solving optimization problems by generating and evaluating alternative variants of the system functioning. The scheme of the integration of GA and simulation is shown in Fig. 1.

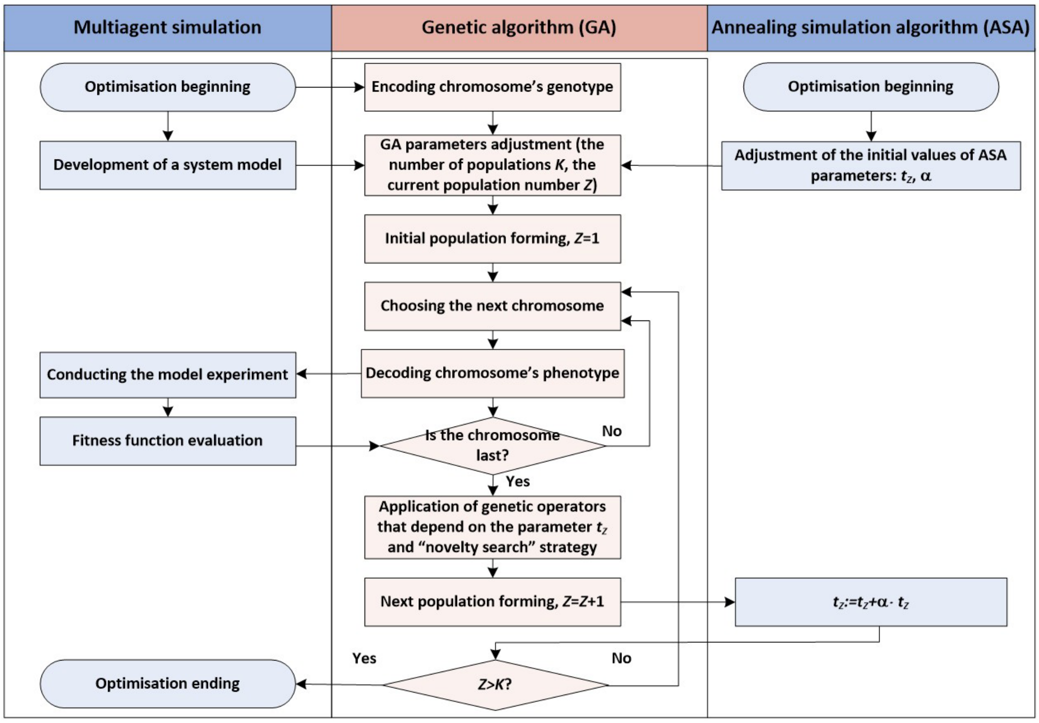

Figure 1: The scheme of the integration of simulation, genetic algorithm, and annealing simulation algorithm.

This scheme differs from existing schemes by modifying the GA in order to improve the quality of the solution found. The genetic algorithm is modified by the annealing simulation algorithm [15] and the novelty search algorithm [16]. In the novelty search algorithm, the measure of the adaptability of an alternative solution to environmental conditions is the originality of the solution, which is determined by numerical transformations of the Hamming distance matrix between chromosomes-solutions. The originality of solutions and their fitness functions (the values of objective functions at the model output) determine the various strategies for the formation of a new population of alternative solutions (a new search space). The annealing simulation algorithm is designed to implement a combination of proposed strategies for the formation of new populations. This algorithm is based on the analogy of the metal annealing process, which results in the appearance of new metal properties.

The formation of a new population occurs by repeating the process of crossing two randomly selected chromosomes of the current population. The choice is made according to the selection probabilities of the first P_i and second P_j chromosomes:

$$P_i = \frac{1}{N}\big(1 - exp(-\frac{1}{t_Z})\big) + p_i^{MSS} exp(-\frac{1}{t_Z}), \tag{1}$$

$$P_j = p_{ij}^{OSS}\big(1 - exp(-\frac{1}{t_Z})\big) + p_j^{MSS} exp(-\frac{1}{t_Z}). \tag{2}$$

Here N is the number of chromosomes in the population; Z is the current population number; t_Z is the parameter of the annealing simulation algorithm (see Fig. 1 for its calculation); p_i^{MSS} and p_j^{MSS} are probabilities of selecting of the chromosomes i and j respectively, the probabilities are proportional to the value of the chromosomes fitness function; p_{ij}^{OSS} is probability of selecting of the chromosomes i and j together, this probability proportional to the weight of the Hamming distance between chromosomes. Hamming distance h_{ij} is the number of positions in the chromosomes i and j, in which the genes of chromosomes differ. The weight of the Hamming distance w_{ij} is calculated by the formula [16]:

$$w_{ij} = \frac{R-1}{\sqrt{L}}\sqrt{h_{ij}} + 1. \tag{3}$$

Here R is the maximum weight of the chromosomes in the pair, L is the chromosome length.

During the work of the hybrid method, as the number of generated populations Z increases, the parameter t_Z increases too, which leads to a change in the strategies for selecting parents for obtaining of the new solutions. At the beginning of the search, for a small value of Z the choice of the most different solutions prevails, one of which is estimated by a high fitness function. This provides a comprehensive search for new solutions through various combinations of existing ones. Then, the strategy is replaced by the choice of both parents whose fitness functions are high. This ensures preservation and improvement of the found solutions with a good result.

4 Application of the hybrid decision-making method

We consider the processes of implementing measures to prevent incidents at the enterprise. Within the research, the following departments with basic settings are distinguished: department of technologists (5 employees); the logistics department (5 employees), the department for resolving of organizational incidents (3 employees), and the change committee (1 employee).

The MRCP model (Fig. 2) has been developed in the CM module of the MEI system. The model is implemented on the resources, which are the queues of incidents to processing with the help of corresponding operations. When describing the processes of the incident prevention measures implementing, decomposition of the model nodes has been used. The agents have been used to distribute operations for the departments and determine the probability of exceeding the estimated time for the operations execution over the actual execution time. The implementation of measures to prevent technological and logistic incidents is described with decomposition into two processes: 1) fulfillment of measures with a normal execution time, and 2) fulfillment of measures with an exceeded execution time leading to the organizational encidents emerging. To fulfill these processes in the distribution agent, different execution queues are formed for the fulfillment.

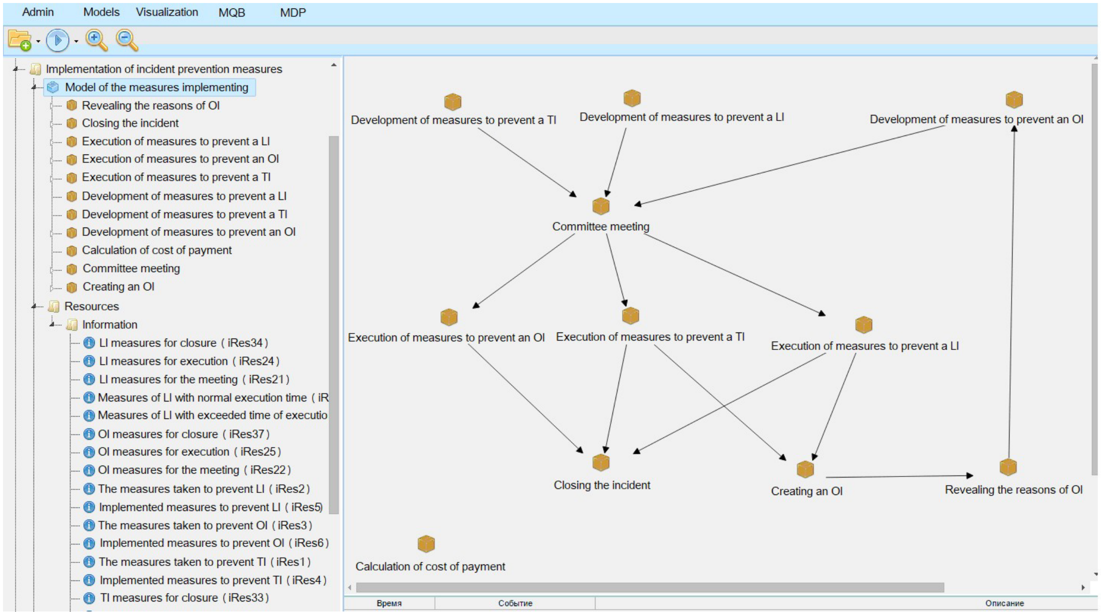

Figure 2: The structure of the model of the incident prevention measures implementing in the CM module of the MEI system.

With the developed model, experiments have been conducted in the PO module of the MEI system. As input to the simulation, statistical data on the number of incidents of each type, the number of incidents executed on time, and the number of incidents executed beyond the deadline have been used. The statistical data have been obtained from the data storage with the help of the query builder and data preparation modules of the MEI system.

The input controllable modeling parameters of the experiments have been changed as follows: the changes committee - from 1 to 2 employees, the logistics department - from 4 to 5 employees, the department of the technologists - from 4 to 5 employees, the department for resolving of organizational incidents - from 2 to 3 employees. As the output information of modeling, the cost of payment of the idle time for employees (it is necessary to minimize) and the percentage of closed incidents (it is necessary to maximize) have been considered.

As a result of a series of experiments, an experiment has been chosen with the best result, for which the cost of payment of the idle time for employees of four departments for two months was 11% less than the cost of payment of the idle time for employees for the basic experiment. For the selected experiment with the best values of the output parameters, the following percentages of closed incidents have been obtained according to the types of incidents (Fig. 3): technological incidents – 48,76%, logistic incidents – 97,95%, organizational incidents – 100%.

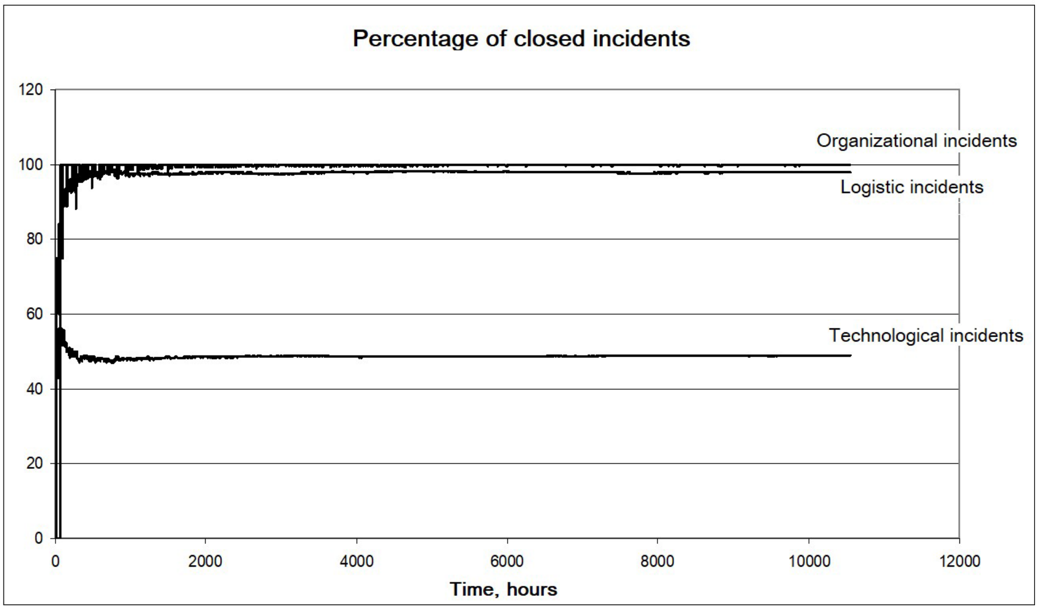

Figure 3: The percentage of closed incidents for the experiment with the best result.

A low percentage of closed technological incidents is associated with a long resolution time for incidents of this type. Often technological incidents are associated with imperfect manufacturing technology. Changing the existing manufacturing technology is a lengthy process that can take from one week to several months. The experiment with the best result is characterized by the following values of the controlled parameters: 4 specialists-technologists, 5 specialists-logists, 2 people from the change committee and 2 specialists of the department for resolving of organizational incidents.

5 Conclusion and future work

The structure of the metallurgical enterprise information system intended for monitoring, tracking, production data collecting and processes modeling has been considered. Storage and data collection in the MEI system are based on solutions in the field of Big Data and industrial automation. The MEI system maintains a multi-user mode and access to the models of production processes and conducting experiments via the Internet.

A hybrid decision-making method based on an integration of the simulation, genetic algorithm, simulation annealing algorithm, and novelty search algorithm implemented in the modeling subsystem of the MEI system is described.

The method has been tested for solving the problem of optimizing the number of enterprise employees. As a result, a solution has been found that permit to reduce the cost of payment of the idle time for employees by 11 percent, while maintaining a high percentage of closed logistic and organizational incidents and an acceptable percentage of closed technological incidents.

The purpose of future work is to expand the MRCP model of the modeling subsystem of the MEI system with numerical methods for solving problems in the context of uncertainty of input information.

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